PROGRAMMABLE OPTICAL QUADRATIC NEURAL NETWORKS

Final Technical Report

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by

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Analytical and experimental investigations of optical quadratic neural networks have been conducted. Results reported include: (1) Development of a polarization-based outer product processor implementing a quadratic neural network, (2) implementation of a photorefractive-crystal based quadratic neural network utilizing feedback for learning, (3) derivation of a statistical parameter which can be used to completely characterize the behavior of linear and higher order Hopfield associative memories and (4) development of a method to reduce the number of interconnections in associative memories while retaining good performance.

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ABSTRACT

Analytical and experimental investigations of optical quadratic neural networks have been conducted. Results reported include: (1) Development of a polarization-based outer product processor implementing a quadratic neural network, (2) implementation of a photorefractive-crystal based quadratic neural network utilizing feedback for learning, (3) derivation of a statistical parameter which can be used to completely characterize the behavior of linear and higher order Hopfield associative memories and (4) development of a method to reduce the number of interconnections in associative memories while retaining good performance.

RESEARCH OBJECTIVES

During the period of the grant (December 1, 1987 - November 30, 1990), the major research objectives have been to perform both analytical and experimental investigations of optical quadratic neural networks. The major areas of investigation have been (1) an electro-optical, outer-product-based architecture for quadratic neural networks employing polarization encoding and utilizing LCTV modulators; (2) optical implementations of quadratic neural networks using photorefractive $BaTiO_3$ crystals to perform the required vector-matrix-vector quadratic operations and using LCTV light modulators to facilitate updating; (3) theoretical/computer analyses and simulations of the characteristics of linear and higher order Hebbian-type neural networks; and (4) techniques for reducing the proliferation of weighting terms in higher order neural networks. Details of the investigations are presented in the following sections and in the publications referenced.

SUMMARY OF RESULTS

In consideration of the large number of journal publications and conference proceedings resulting from this research, we will briefly summarize the major results obtained in this section, with references made to the appropriate publications.

1. Electro-Optical Implementation of a Weighted Outer Product Processor Using Polarization Encoding

This project investigated the design and applications of a weighted outer product processor based on polarization encoding techniques. The processor implements a general quadratic polynomial with bipolar coefficients as the outer product of a vector $\underline{x}$ followed by a generalized inner product with a matrix of weights (coefficients of the polynomial) $\underline{W}$. The result is obtained as the element-by-element multiplication between the outer product matrix and the weight matrix followed by spatial integration. The architecture is shown in Fig. 1.[1]

Here, the LCTV modulators 1 and 2 perform the outer product, while LCTVs 3 and 4 perform the weighting on the outer product matrix. The outputs are detected by the photodiodes and are read into a computer where the information can be used to update the weights, as in the case of an iterative network. By using the properties of the polarization-encoding technique, we have been able to reduce the space-bandwidth product to one-fourth of what would normally be required in systems operating with bipolar

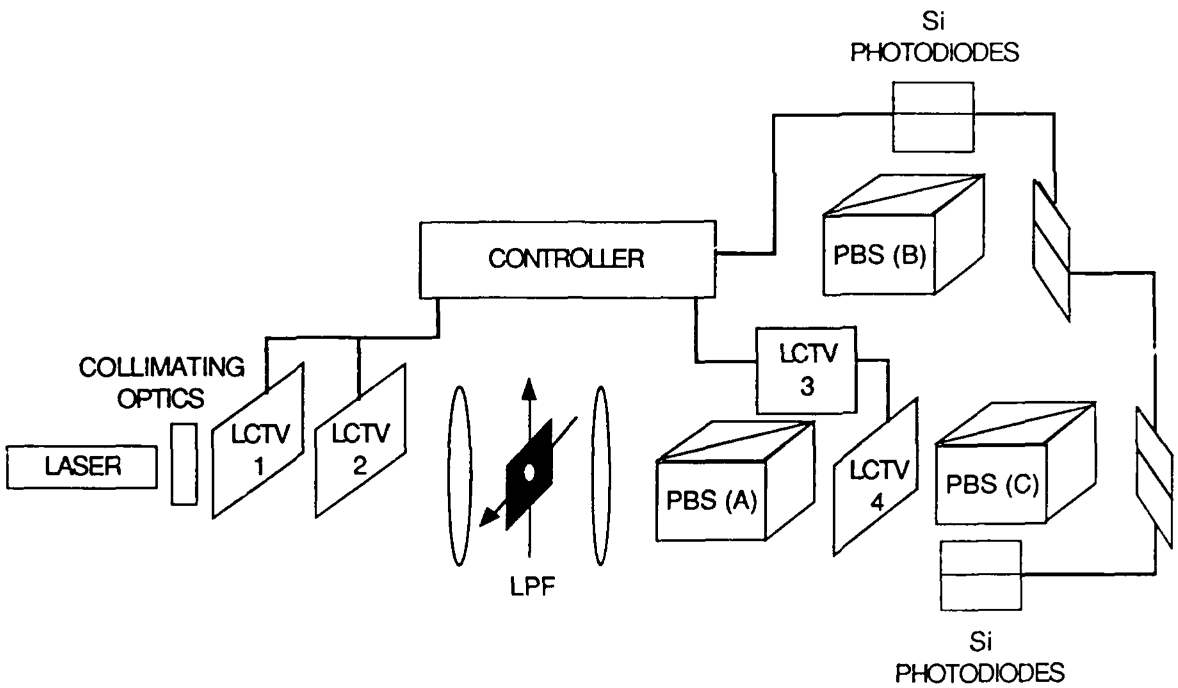

Fig. 1. Polarization-encoded weighted outer product processor.

numbers. A second system, with only one LCTV for the outer product and one for the weights, was also designed and tested. This system traded off increased electronic preprocessing for simpler optics.

Among the applications investigated using the outer product processor was a quadratic neural network with learning. The network was tested on problems such as the familiar Exclusive-OR problem and pattern recognition problems. As expected, it demonstrated a superior performance when compared with linear neural nets. The polarization-encoded optical outer product processor, which has also been shown capable of optical polynomial

evaluations, was also applied to generate Walsh and Haar transforms and optical logic. System characteristics such as throughput, speed, resolution, dynamic range, and cascadability were also investigated.[2]

2. Optical Quadratic Neural Networks Using Barium Titanate

A. Optical Quadratic Processing Units

Because quadratic neural networks have a number of advantages (i.e. increased capacity and increased learning rate) over linear neural networks,[3] an optical quadratic neural network has been designed and successfully implemented. The network uses the quadratic decision function (in vector-matrix-vector form)

$$y = \mathbf{x}^{\mathbf{T}} \mathbf{W} \mathbf{x} \,, \tag{1}$$

where **W** is the interconnection weight matrix and **x** is the neural network input vector.[4]

Optical four-wave mixing in electrooptic barium titanate ($BaTiO_3$) was used to accomplish the required multiplication operation. The optical properties of $BaTiO_3$ were characterized in our laboratory by Otto Spitz in his Master's thesis.[5] Afterwards, Greg Henderson applied the photorefractive property of the crystal to implement the result of Equation (1) optically.[6]

The process of four-wave mixing is shown in Fig. 2. Three laser beamlets are incident onto the $BaTiO_3$ crystal. The **x** matrix is encoded onto one pump beam, and the $\mathbf{x}^{\mathbf{T}}$ matrix is encoded onto the counterpropagating pump beam. The **W** weight matrix is encoded onto the probe beam. The output is a phase-conjugate beam which is proportional to the product of the three incident beams. With a one-neuron processor, a 4-element input vector, and a 4 x 4 binary weight matrix, the system was able to achieve 13.8 dB power signal-to-noise ratio. Then, angle multiplexing was used to increase the number of neurons. However, the power signal-to-noise ratio was reduced to 9.54 dB. Thus, spatial multiplexing

was chosen over angle multiplexing for increasing the number of neurons that can be packed inside a single $BaTiO_3$ crystal.

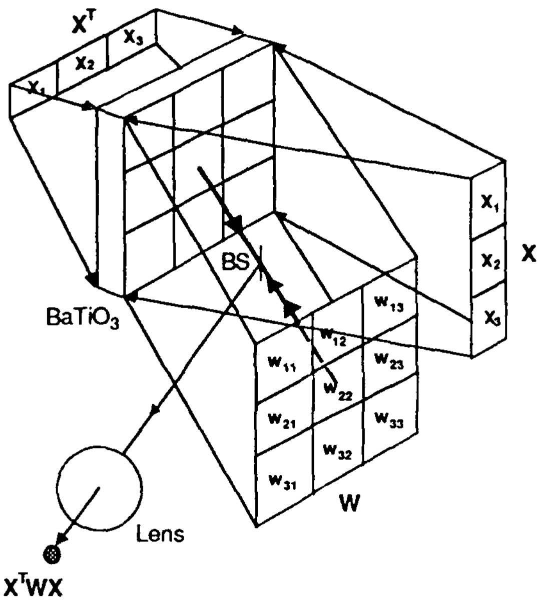

Fig. 2. Four-wave mixing in Barium Titanate ($BaTiO_3$). The **X** *and* $\mathbf{X^T}$ *matrices are encoded on the counterpropagating pump beams while the* **W** *matrix is encoded on the probe beam. The phase-conjugate output is summed by the lens to generate the result* $\mathbf{X^TWX}$.

B. Optical Quadratic Perceptron Neural Network

This project, completed by Alex Huynh, investigated a closed-loop neural network constructed from the previously discussed optical quadratic neurons. The quadratic network can dramatically increase the speed of convergence because the inputs are pre-correlated in pairs before being introduced to the single layer of processing neurons. An operational quadratic neural network with

a feedback path has been successfully realized after some electronics (a computer, video cameras, scanrate converters, etc.) were interfaced with the optics. For training the neural network, the popular Perceptron learning algorithm in its quadratic form was chosen.[7] To implement this algorithm, each neuron, composed of both positive and negative polarities, is spatially multiplexed onto the $BaTiO_3$ crystal.

The two-neuron architecture developed by Alex Huynh is shown in Fig. 3. As previously discussed, the vector-matrix-vector quadratic product operation is performed by four-wave mixing in $BaTiO_3$. The phase-conjugate output emerges from the crystal and is reflected by a beamsplitter (BS3) onto the charge-coupled device (CCD) camera and then digitized into the computer. To allow easy modifications, the input and interconnection matrices are now generated on a Macintosh computer and written to a monochrome liquid-crystal television (LCTV). The computer's tasks also include thresholding the $BaTiO_3$'s output, comparing this thresholded output with a specified target value, and altering the interconnection matrix accordingly. The neural network iterates until convergence is achieved.

During the performance tests, the system was configured as two bipolar neurons of 3 x 3 elements each. The network converged to the desired output values within 50 iterations for all 2-bit target permutations. Although two neurons were tested, the number of neural processors that can be placed inside a single barium titanate crystal has been experimentally increased to four and may be theoretically increased up to the number of pixels of the LCTV.

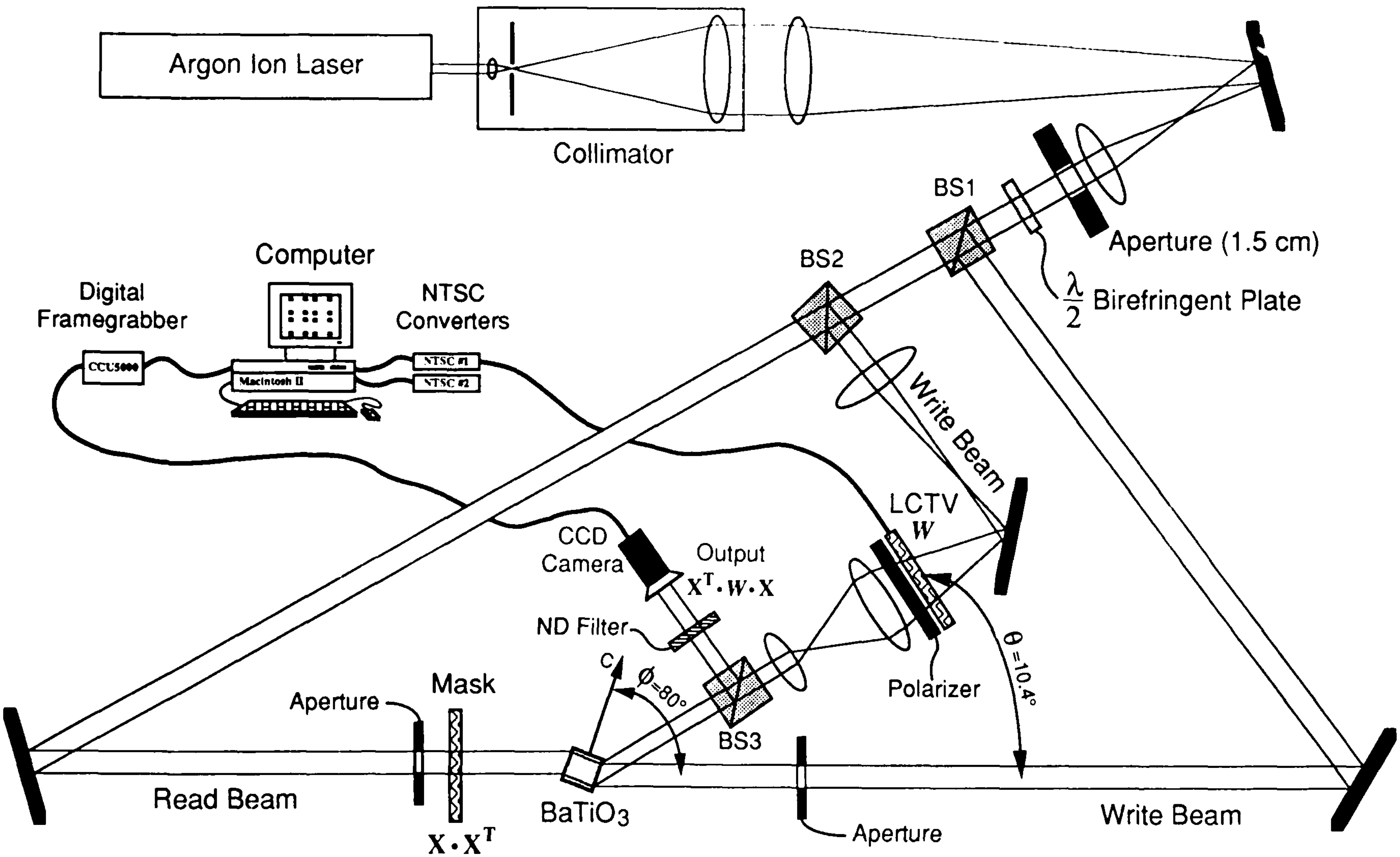

Fig. 3. BaTiO3-based quadratic network with learning.

In summary, an operational optical quadratic Perceptron neural network has been developed with the capabilities to learn and classify binary patterns.

3. Determination of Hopfield Associative Memory Characteristics

A. Introduction

It has been previously shown by Hopfield[8] that associative memories based on the Hopfield neural network model (which we call first order Hopfield associative memories, or HAMs) are capable of storing information, usually specified by N-dimensional binary vectors, in a distributive way as well as recalling the complete stored information when presented with a noisy input (error-correction). Through a "learning" process utilizing the sum of outer products algorithm,[9] information is learned as stable states in the self-feedback Hopfield network. The recall process starts with a probe input and will iterate until a stable state is reached. The number of storable stable states, however, is limited by the number of neurons (N) and the degree of error-correction desired. Previously this issue of memory capacity had been investigated, based on the assumption of $N \rightarrow \infty$, by numerous researchers.[10,11,12] Thus, if N is small the error in their capacity predictions may be significant. In addition, no specific procedure or proof for calculating the attraction radii of HAMs has been given in the past.

During this funding period, a new statistical method using a single signal-to-noise parameter (which we call C) was developed as a tool to study both first order[13,14,15] and higher order HAMs.[16,17,18] The C parameter method, which emphasizes the importance of specifying the required network convergence probability, is found to characterize the scaling properties of

HAMs more accurately and efficiently than other researchers' methods.[10,11,12]

B. Mathematical Formulation

Given N, M (the number of stored vectors), and b (the number of error bits in the probe vector), the C parameter for a p_{th} order HAM is found to be

$$C = \frac{(N-2b)^p}{\sqrt{\dfrac{MN^p(2p)!}{2^p p!}}}.$$

The probability that a neuron will hold an incorrect bit after a single update cycle is calculated as

$$\eta = P(\text{incorrect}) = \frac{1}{2}\int_0^1 P(\beta)\, d\beta, \quad \text{where}$$

$$P(\beta) = \frac{2C}{\sqrt{2\pi}\beta^2} \operatorname{Exp}\left[-\frac{C^2}{2\beta^2}\right].$$

The characteristic of these two equations is that they are invariant in their form as p changes. Once the values of N, M, b, and p are given, the value of C is determined and η can be calculated accordingly. Finally, with the approximate joint independence[14,19] which exists among all neurons when the memory performs its update synchronously, the value of η solely determines the convergence probability of the network. Thus, the essential ingredient of the C parameter method is the property of

1-to-1 mapping of the C parameter to the convergence probability of HAMs.

C. Applications

With the aid of the C parameter, we obtained the following key scaling properties for various versions of the HAM.

(1) The memory capacity and the attraction radius of the direct convergence (one-step) HAM, in which the initial vector is required to precisely converge to the stored vector in one iteration, can be predicted. It has been shown that,[10,14] when storing M' vectors, where M' $\leq$ the memory capacity M, the Hopfield network will likely converge to a stored vector after the first iteration. Therefore, the capacity derived for the direct convergence HAM when $N \rightarrow \infty$ is also the asymptotic capacity for the Hopfield network.

(2) The memory capacity and the attraction radius of the indirect convergence HAM, in which a specified percent error ε is allowed after multiple iterations, can be computed. Both the cases of first order[13,14,15] and higher order HAMs[16,17,18] were investigated for (1) and (2).

(3) In (1) and (2) we also showed, using the close tie between convergence probability and the C parameter, that given a fixed convergence probability, the memory capacity can be traded for an increase of attraction radius, or generalization capability, and vice versa.

(4) Figures of merit for the performance of HAMs have been formulated.[15] Two statistical parameters that can be used to

determine the performance of arbitrary order HAMs were developed. The principle involves using two figures of merit, ε/η and ηN, to determine the convergence probability for indirect convergence and direct convergence HAMs described in (1) and (2). Given η, the parameter ε/η determines the capability of converging iteratively to at most εN bits away from the stored vector, where $0< \varepsilon<0.5$. We showed that the indirect convergence probability $P_{ic}\approx1.0$ for all HAMs having $\varepsilon/\eta>20$. On the other hand, if precise convergence to the stored vector in one step is required, the parameter ηN is used to determine the probability of direct convergence, P_{dc}.

Since these two parameters, ε/η and ηN, can determine the convergence probability of the indirect convergence and direct convergence HAMs, they in turn can determine the memory capacity for these HAMs. This argument means that in the case of indirect convergence, given any two of the parameters ε, M or N, we can find the third parameter. Similarly, for the case of direct convergence, given any two of the parameters P_{dc}, M or N, we can find the third parameter.

(5) Unique characteristics of HAMs with nonzero-diagonal terms in the memory matrix (which we call NZAM) were determined. We applied the C parameter method in studying the unique characteristics of this special version of the HAM. It has been shown that for an outer-product type network, e.g., the one investigated by Hopfield[8], the ratio $M/N=\alpha$ holds for small α's, e.g., $\alpha\approx0.15$. As in the HAM, the memory matrix of the NZAM is constructed to store M vectors based on the outer-product learning algorithm, but all the diagonal terms of the memory matrix are set

to be M. Assuming the input error ratio $\rho=0$, we theoretically proved[20] a surprising simulation result by Stiles *et al.*[21] that in the NZAM the probability of successful recall, P_r, steadily decreases as α increases, but as α increases past 1.0, P_r begins to increase slowly. In particular, if P_r is expressed as a function of α, there exist double roots α_1 and α_2 such that $\alpha_1\alpha_2=1$ and $P_r(\alpha_1)=P_r(\alpha_2)$. This is unique in the sense that it occurs only in the NZAM of first order.

Even when $0<\rho\leq0.5$, the NZAM is unique in its own way and results in special network behavior due to the nonzero diagonal terms. The property $P_r(\alpha_1)=P_r(\alpha_2)$, however, no longer exists in this case. When $0<\rho\leq0.5$, the network exhibits strong error-correction capability if $\alpha\leq0.15$ and this capability is shown to rapidly decrease as α increases. The network essentially loses all its error-correction capability at $\alpha=2$, regardless of the value of ρ. In the extreme case of $\alpha>>1$, the network acts like an all-pass filter and the number of stable states increases to 2^N. When $0<\rho\leq0.5$, and under the constraint of $P_r>0.99$, the tradeoff between the number of stable states and their attraction force was analyzed and the memory capacity was shown to be 0.15N at best.

4. Reduction of Interconnection Weights in Higher Order HAMs

The main goal of this project was to apply the C parameter technique to eliminate redundant interconnection weights in higher order HAMs. It has been shown that the memory capacity of higher order HAMs can increase rapidly as the order of the network p increases.[16,22] But the problem with higher order HAMs is that the number of interconnection weighting terms also increases very rapidly with the number of inputs N and the order p, and it becomes unacceptably large for use in many situations. In general, the number of independent weighting terms in the pth order expansion is approximately $(N^{p+1})/p!$. Previous techniques for dealing with this proliferation problem involve using *a priori* knowledge of the problem domain to eliminate the terms which have a small likelihood of being useful.[23] This prelearning method produces specialized networks which are useful in a limited domain, such as geometric invariance in pattern recognition. As for the case of HAMs, no efficient method for tackling the proliferation problem has previously been seen.

During this funding period, we showed that among all connection weights $\mathbf{T}$ based on the outer-product rule, $-M \le \mathbf{T} \le M$, principal weights called Tpr, $\sqrt{M} \le |\mathrm{Tpr} \in \mathbf{T}| \le M$, carry more information than the others.[17] We proved that HAMs using only these principal weights are capable of achieving good recall results. Using only Tpr weights can result in a savings of more than 50% of the original number of connection weights.

We have proposed a 3-layer neural network that explores the advantages of the principal weights described above. The proposed

network includes (1) an input layer, (2) a hidden layer that contains product units,[24] and (3) an output layer that contains ordinary sigmoidally-thresholded summing units. The network operations consist of three phases: (1) preprocess the prescribed associative vectors and select the principal weights T_{pr}; (2) create the required number of product units and interconnections according to the results obtained in (1); and (3) train the network using the backpropagation learning algorithm until high memory recall accuracy is achieved. We are definitely encouraged by the results obtained to date on this network, in particular the tremendous improvement in the training speed and the efficient implementation. We believe that further investigation of this network is of great interest in the field of associative memory and pattern recognition.

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RESEARCH PERSONNEL (1987-1990)

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COMPLETED THESES AND DISSERTATIONS (1987-1990)

1. J.H. Wang, "Characterization of First and Second Order Hopfield Neural Networks," M.S. thesis, Dept. of Electrical Engineering, Texas Tech University, Lubbock, TX August 1988.

2. A.P. Ittycheriah, "An Optical Outer Product Processor and its Applications," M.S. thesis, Dept of Electrical Engineering, Texas Tech University, Lubbock, TX, May 1989.

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4. J.H. Wang, "Higher Order Neural Network Associative Memories," Ph.D. dissertation, Dept. of Electrical Engineering, Texas Tech University, Lubbock, TX, May, 1991 (expected).

5. A.V. Huynh, " An Optical Quadratic Perceptron Neural Network", M.S. thesis, Dept. of Electrical Engineering, Texas Tech University, Lubbock, TX, August, 1991 (expected).

RECORD OF JOURNAL PUBLICATIONS ON AFOSR 88-0064

Journal Papers Published

1. "An Optical Quadratic Processor Using Four-Wave Mixing in $BaTiO_3$" Optics Letter, 14, 770-772 (1989)(G.N. Henderson, J.F. Walkup and E.J. Bochove).

2. "Outer-Product Processor Using Polarization Encoding," Applied Optics, 29, 275-283 (1990)(A.P. Ittycheriah, J.F. Walkup and T.F. Krile).

3. "Determination of Hopfield Associative Memory Characteristics Using a Single Parameter," Neural Networks, 3, 319-331 (1990)(J.H. Wang, T.F. Krile, and J.F. Walkup)

Journal Papers Accepted for Publication

1. "On the Characteristics of the Auto-Associative Memory with Nonzero-Diagonal Terms in the Memory Matrix," (to appear in Neural Computation, 1991) J.H. Wang, T.L. Jong, T.F. Krile, J.F. Walkup.

2. "An Optical Matrix Vector Multiplier Project," (to appear in IEEE Trans. on Education, Feb. 1991) A.P. Ittycheriah, J.F. Walkup and T.F. Krile.

Journal Papers Submitted for Publication

1. "Determination of Higher Order Associative Memory Characteristics Using a Single Parameter," (submitted to IEEE Trans. on Neural Networks) J.H. Wang, T.F. Krile and J.F. Walkup.

2. "The Generalized Bilinear Transform in Optical Processing," (submitted to J. Opt. Soc. Am-A) S.H. Lin, T.F. Krile and J.F. Walkup.

3. "Noise Effects in Optical Hopfield - Type Neural Networks," (submitted to Applied Optics) T.L. Jong, J.F. Walkup and T.F. Krile.

Journal Papers in Preparation

1. "An Optical Quadratic Perceptron Neural Network Using a Photorefractive Crystal" (in preparation for Optics Letters) A.V. Huynh, J.F. Walkup, and T.F. Krile.

2. "Encoding for Error Correction in Optical Computing," (in preparation for Applied Optics) S.A. Ellett, J.F. Walkup, and T.F. Krile.

INTERACTION ACTIVITIES (1987-1990)

Papers Presented at Major Professional Meetings

1. S.H. Lin, T.F. Krile, and J.F. Walkup, "Electro-optical Implementations of Programmable Quadratic Neural Networks, SPIE Vol. 882, (presented at O-E/LASE '88, Los Angeles, CA, Jan 1988).

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8. G.N. Henderson, J.F. Walkup and E.J. Bochove, "Optical Quadratic Processing in Photorefractive $BaTiO_3$," Opt. Soc. of Am. Ann. Mtg., Orlando, FL, October 1989.

9. A.T. Smith and J.F. Walkup, "Electro-Optical Implementations of the Alternating Projection Neural Network (APNN)," Opt. Soc. of Am. Ann. Mtg., Orlando FL, October 1989.

10. S.G. Batsell, J.F. Walkup and T.F Krile, "Fundamental Noise Limitations in Optical Linear Algebra Processors," Opt. Soc. of Am. Ann. Mtg., Orlando, FL, October 1989.

11. J.H. Wang, T.F. Krile, and J.F. Walkup, "Figures of Merit for the Performance of Hebbian-type Associative Memories, "Proc. of Internatl. Joint Conf. on Neural Networks, San Diego, CA, Jul 1990, 833-838.

12. S.G. Batsell, J.F. Walkup, and T.F. Krile, "Bounds on Achievable Accuracy in Analog Optical Linear Algebra Processors," Internatl. Congress on Optics-15, Garmisch-Partenkirchen, Federal Republic of Germany, August 1990.

13. S.A. Ellett, J.F. Walkup, and T.F. Krile, "Encoding for Error Correction in Optical Computing," 1990 Annual Mtg., Opt. Soc. of Am., Boston, MA, November 1990.

14. A.V. Huynh, J.F. Walkup, and T.F. Krile, "Optical Quadratic Perceptron Neural Network," 1990 Annual Mtg., Opt. Soc. of Am., Boston, MA, November 1990.

Other Interaction Activities

1. Served as Chairman of Education Council, Optical Society of America, 1987-88 (J.F. Walkup).

2. Lectured on "Optical Computing," at First International School and Workshop on Photonics, Oaxtepec, Mexico, July 4-8, 1988 (J.F. Walkup).

3. Faculty development leave research on optical neural networks and optical computing, Computer Engineering Dept., Wright State University, Dayton, OH (T.F. Krile, 15 July 1988-15 July 1989).

4. Interacted with Prof. Robert J. Marks II, University of Washington on optical neural networks as part of a joint U. of W./Texas Tech University SDI/ONR research project on Accuracy Limitations in Optical Computing (J.F. Walkup and T.F. Krile).

5. Invited lecturer, Optical Engineering Society of the Republic of China (several universities in Taiwan), June 1989 (J.F. Walkup).

6. Invited speaker, Texas Systems Day, Rice University, 1989 (J.F. Walkup).

7. Invited by Soviet Branch of the World Laboratory to present lectures at the following institutes in Leningrad, USSR, (June 1990): Leningrad Technological Institute; Institute of Aviation Instrument Making; Science and Technology Corporation; Institute of Precision Mechanics and Optics; S.I. Vavilov State Optical Institute (J.F. Walkup).

8. Organizing Committee, NSF-sponsored Workshop on Opto-electronics Education, Colorado Springs, CO, July 1990 (T.F. Krile).

9. Vice-Chairman, 1989 Gordon Research Conference on Holography and Optical Information Processing, Plymouth, NH, August 1989 (J.F. Walkup).

10. Chairman, 1991 Gordon Research Conference on Holography and Optical Information Processing, Plymouth, NH, June 1991 (J.F. Walkup).

SIGNIFICANT ACCOMPLISHMENTS

1. Completed investigation of a polarization-encoded outer product processor for implementing quadratic neural networks and other applications.

2. Achieved vector-matrix-vector real time processing operations in photorefractive $BaTiO_3$ crystals using 4-wave mixing. Also investigated other optical signal processing operations in $BaTiO_3$.

3. Introduced computer controlled LCTV modulators (for updating) in a feedback loop to implement an optical quadratic processor based on photorefractive barium titanate crystals.

4. Developed a signal-to-noise ratio parameter-based performance characterization of linear, quadratic and higher-order Hopfield associative memories (HAMs).

5. Found a method to reduce the number of interconnection terms in HAMs while retaining their memory storage and generalization capabilities.